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Cancer Detection and Categorizing Using Convolutional Neural Network from the CT Scan Images

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***Abstract* - With approximately 10 million deaths and 208.9 billion dollars in treatment costs in 2020, cancer has recently risen to the top of the list of killers in the globe. Additionally, more individuals are receiving cancer diagnoses each year; by 2040, there will be 27.5 million new instances of cancer annually. "Machine learning" is a subfield of artificial intelligence that employs a variety of statistical, probabilistic, and optimization techniques to enable computers to "learn" from prior knowledge and locate challenging patterns in huge, noisy, or complex data sets. Particularly well-suited for this capability are medical applications, especially those that depend on complex proteomic and genomic data. Thus, the detection and diagnosis of cancer make extensive use of machine learning. The objective of the current study is to create a deep learning (DL) instrument that can categorizes CT scan images of the kidneys and brain into a) kidney tumour, b) kidney normal, c) glioma, d) meningioma, and e) pituitary tumour (CNN). The 25000 photos in the dataset, which was gathered from Kaggle, were divided at random into training and testing data. Images were utilised for teaching 70% of the time and testing 30% of the time. To lessen skewness and enhance CNN performance, the images were reduced in size to 150*150 pixels, randomly rotated horizontally, transformed to grayscale, and had their colour ranges standardised to [0, 1]. Then, the Python modules pytorch and torchvision were used to build the CNN model. There were 3 pooling layers and 3 convolutional layers employed. For activation, the ReLU function was utilised. 50 epochs were used to test the CNN model, however PyTorch selects the number of epochs with the highest degree of testing accuracy. The actual label of the image is contrasted with the output label. Training accuracy for our model was 0.7895, and testing accuracy was 0.7561. Our study anticipates that doctors will use this tool to automate the process of finding eye diseases. This might speed up the process and encourage early detection.**

Keywords: Cancer detection, Brain Cancer, Kidney Cancer, Convolutional Neural Network, CT Scan Images

I. INTRODUCTION

Cancer is caused by the deviation of cells from the cell cycle caused by uncontrolled growth and rapid cell division [1]. Normally, the cell cycle entails the growth of cells followed by cell division to form two daughter cells or maturation in which cells specialize and lose the ability to become new cells. However, cancer cells don't stop growing and dividing as they lack the ability to mature, forming lumps (tumours) that grow in size, and into key blood vessels, nerves and organs(impairing their function) [2]. This unregulated growth is a result of the mutation of protooncogenes (genes involved in the production of proteins essential for “cell growth, division and other processes”) into oncogenes. Oncogenes can replicated and translate continuously, causing cancer [3].

In recent years, cancer has become one of the leading causes of death in the world with it accounting for over 10 million deaths and 208.9 billion dollars in treatment spending in 2020 [4]. Furthermore, the number of individuals diagnosed every year has also been rising and is estimated to grow to 27.5 million new cancer cases every year by 2040 [5]. Due to this, cancer is considered as a major global health and financial concern, especially in developing countries.

A. Motivation and novelties

The present study aims in developing an intelligent system to detect and classify brain and kidney cancer from the CT scan images. In this regard a deep learning (DL) based Convolutional Neural Network (CNN) is developed that is capable of detecting and categorizing the brain and kidney cancer into different classes.

II. Literature review

With the expert advice in the domain of the research and literatures reviewed, it is concluded that there is a great potential of deep learning in cancer diagnosis and prognosis. Diagnosis of cancer is relatively difficult due to some cancers being hard to spot (requiring trained eyes and techniques) and other forms of the disease being so rare that not a lot of research is conducted on them [6]. This is very detrimental as early diagnosis of cancer provides the highest possibility of survival [7]. This is because early detection provides the best chance for successful treatment and lower costs of care, whereas delayed detection is associated with lower chances of survival and relatively higher costs of care [6].

Since images have intrinsic problems including inadequate contrast, noise, and a lack of visual appreciation, tools have been developed to produce improve images. CNN, machine learning (ML), and artificial intelligence (AI) are now the three areas of the healthcare research that are expanding the fastest [8–12]. AI and ML research are focused on reducing the need on human intellect by enhancing technological solutions to solve complex challenges [13–15].

DL is a state-of-the-art techniques that includes artificial neural networks (ANN), DNN (deep neural networks), RNN (recurrent neural networks), DBN (deep belief networks), and CNN. DL tools are widely applied in computer vision, audio recognition, speech recognition, social network filtering, natural language processing, machine translation, drug design, bioinformatics, medical image analysis, materials scrutiny, histopathological diagnosis, and board game programs [16–18]. The diagnostic accuracy and efficacy of cancer detection can be improved by using DL algorithms [19].

However, a method known as digital pathology (DP) allows for the digitisation of histology slides in order to provide high-resolution images. These digital images are used for detection, segmentation, and classification through the application of image analysis tools. Understanding patterns for image classification requires additional steps, such as digital staining, when using CNNs [20].

CNN offers more opportunities for medical imaging research than only deep CNN's ability to extract imaging features. In fact, using CNN for synthetic image rendering is a second area that can aid medical research. Acceptable colour and textural qualities are established to help with mitotic count-based selection of ROIs at lower resolution, according to a study by Wahab and Khan [21] utilising MF-CNN (multifaceted fused-CNN) and a hybrid descriptor. In order to recognise dynamic patterns, the MF-CNN recognises many aspects of the input image. It employs the global image texture to create a hybrid descriptor and mitoses, extracts, and hand-crafted features from ROIs to train a classifier that assigns WSIs scores. In domains where it is difficult for domain experts to design effective features, CNNs are opening up to unthinkable eventualities. The naive application of CNNs may not be successful, according to Gravina et al. [22], since "medical images are more extraordinary than typical images." Mammographic lesion segmentation has been demonstrated to be a valuable source of information since it may aid in both the extraction of shape-related features and the precise localization of lesions.

Tsochatzidis et al. [23] tested the accuracy of mammogram-based breast cancer diagnosis using CNN. They demonstrate how diagnostic performance assessment is done using two mammographic mass datasets, such as DDSM-400 and CBIS-DDSM, with varying degrees of ground truth segmentation map accuracy. Malathi et al. [24] used a computer-aided diagnostic (CAD) system for mammography to enable the first detection, evaluation, and treatment of breast cancer. They talked about investigating a breast CAD design that fuses traits using deep learning of the CNN. The RFA (random forest algorithm) has the highest precision and fewer error than the CNN classifier, according to the results (95.65 percent). The deep belief network is used to study the irregularity of breast representations (DBN). The supplied work procedures activate contour segmentation, which may be requested by the DBN, to identify the anomalous picture. According to Desai and Shah [25], a thorough analysis of the architecture and functioning of each network is performed, and the performance of each network is then evaluated based on how accurately it diagnoses and classifies breast cancer. When it comes to the detection and diagnosis of breast cancer, CNN is seen to offer a little bit more precision than MLP.

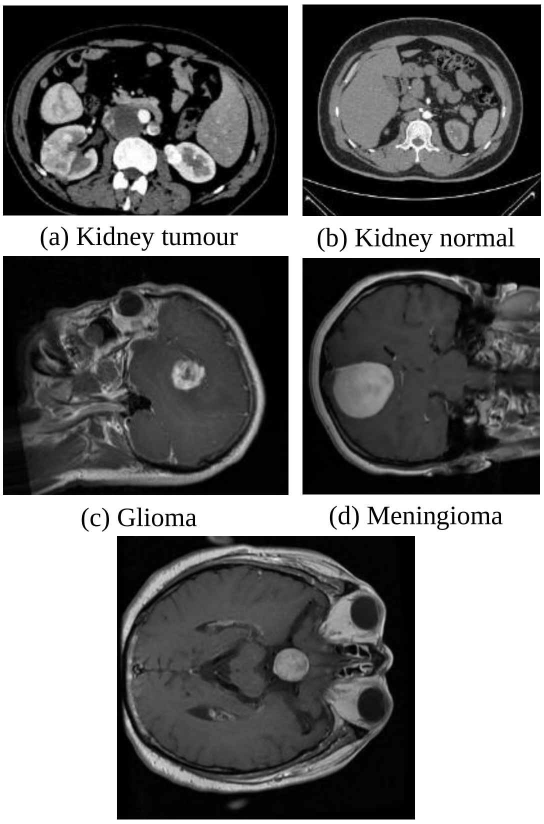
III. Materials and Methods

In this section of the paper, a brief description of the data and methodology adopted is given

A. Data acquisition

The dataset, “multi-cancer dataset”, was from Kaggle [26]. The dataset comprises of images of 9 different types of cancer. The dataset is images of cancer both digital as well as CT scan images. The aim of the paper is to classify and categorize the brain and kidney cancer from CT scan images. The brain cancer has three labels namely Glioma, Meningioma and Pituitary Tumor

Lung Adenocarcinoma, Lung Benign Tissue and Lung Squamous Cell Carcinoma. On the other hand Kidney cancer has two labels namely Normal and Tumor. There are a total of 25000 CT scan images belonging to all the five labels of lung and kidney cancer. Of the total images 70% images are used for training and remaining 30% are used for testing and validation. Figure 1 shows the one CT scan image from each label.



(a) Kidney tumour (b) Kidney normal (c) Glioma (d) Meningioma (e) Pituitary Tumor

Figure 1: CT scan image from label (a) Kidney tumour, (b) Kidney normal, (c) Glioma, (d) Meningioma and (e) Pituitary Tumor

B. Methodology

Using CT scan imaging data, the Convolutional Neural Network (CNN) classification model can identify and classify cancer. A powerful deep learning (DL) technique that is frequently used for classifying picture datasets is CNN. These are the top algorithms that are currently on hand for automatically analyzing and classifying pictures. The main distinction between CNN and its forerunners is that it uses ML to identify crucial elements without involving humans.

Training of the CNN model

In DL, the model training technique entails feeding data to the DL algorithm, in this case CNN, to aid in its recognition and learning of the best values for all pertinent variables [27]. In order to compare the processed output to the sample output, the training model is utilized to run the input data through the algorithm. The correlation's findings are applied to the model to change it. Model fitting is the name of this iterative procedure. For the model to be accurate, the training dataset or validation dataset must be precise. The steps for training a CNN model includes:

Convolution layer

The CNN model's convolutional layer extracts features from the image while removing noise. A third function (ψ), which explains how the shape of one is changed by the other, ψ is created by joining the filter and image matrix, which are generally denoted by the letters f and g. The dot product of f and g, which is provided in Eq. (1), is the formula for calculating the convolutional matrix of the proposed CNN model. Figure 2 displays a graphic representation of the convolution layer.

$$f \,.\, g = \psi \tag{1}$$

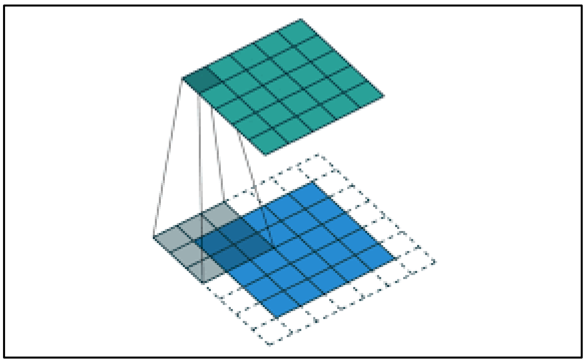


Figure 2: Visual representation of a convolution layer

Activation function

In models of neural networks, the activation function converts the weighted sum of each node is input to output for that layer of the network. In the developed CNN model, rectified linear unit (ReLU) is used as the activation function. It is written mathematically as:

$$\left.\begin{aligned} f(x) &= 0, \quad if\ x \in (-\infty, 0] \\ f(x) &= x, \quad if\ x > (0, +\infty) \end{aligned}\right\} \tag{2}$$

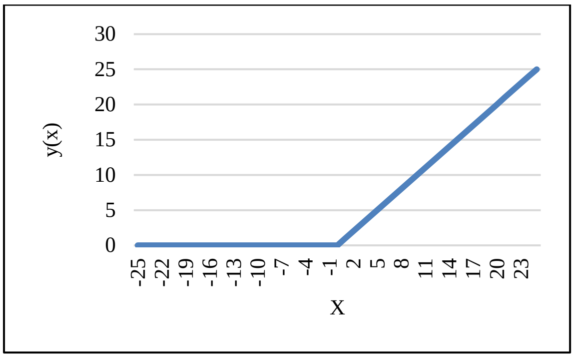


Figure 3: Visual representation of ReLU layer.

Pooling operations

The feature maps' dimension is reduced by the pooling method, which also reduces the number of parameters that must be learned and the quantity of network processing required. The pooling layer is crucial because it summarizes the features that are present in a particular area of the feature map created by the convolution layer. There are two options: maximum pooling and average pooling. Max pooling has been used in the current research endeavour since we are interested in the image's lighter pixels.

Layer stacking operations

Layer stacking continually applies convolution, activation, and pooling processes until the result is a reduced matrix of the input image. To reduce the loss values and boost accuracy, we used three layers. Although it takes a long time, accuracy has improved. Our model would have been more prone to overfitting if we had utilized more layers.

Fully connected layer

Neurons from the preceding levels are fully coupled to one another in the fully connected (FC) layer. The output or label of the input class is predicted by the FC layer. The input label is categorized using several activation functions in multi-class issues.

Classification

A step after categorization is classification. The CNN model divides the pictures of eyes in the study into the following five classes: (i) Kidney tumour, (ii) Kidney normal, (iii) Glioma, (iv) Meningioma and (v) Pituitary Tumor. Figure 4 displays a diagrammatic depiction of the suggested CNN model.

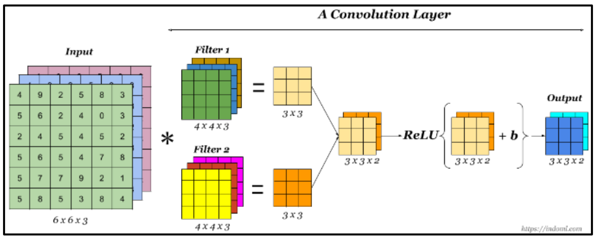


Figure 4: The CNN network

Testing the CNN model

The 30 % of the CT scan images are used to test the model. Although 50 epochs are initially specified, the program save the parameter settings of that epochs with the best testing accuracy. The actual label of the image is contrasted with the output label.

IV. Results and Discussions

This study uses the torchvision DL library to create the CNN model. The CNN method is programmed on a Windows PC with 8 GB of 1600 MHz DDR3 memory and an Intel Core i5 dual-core processor running at 1.8 GHz.

A. Results

To categorise the Kidney tumour, Kidney normal, Glioma, Meningioma, and Pituitary Tumor classes using CT scan imaging data, the CNN model is run for 50 epochs with 15 iterations per epoch and one iteration per epoch for validation. Plotting the accuracy graphs for the training and test sets enables performance evaluation of the CNN model. In order to classify and predict diseases using CT scan pictures of kidney and brain cancer, the parameter values for the CNN with the epoch that displayed the maximum test accuracy were kept.

The training and testing accuracy graphs for the CNN model are shown in Figures 5 and 6, respectively. The CNN model's training accuracy started off at 0.2339 and increased to 0.8246 in the 50th epoch. The CNN model's testing accuracy, on the other hand, increased from 0.4634 in the first epoch to 0.707 in the 50th. However, the highest accuracy is seen in the 48th epoch, with a testing accuracy of 0.7561. The 48th epoch CNN parameter settings are kept as a result. The training accuracy graph and the testing accuracy graph for the developed CNN model are shown in Figures 5 and 6, respectively.

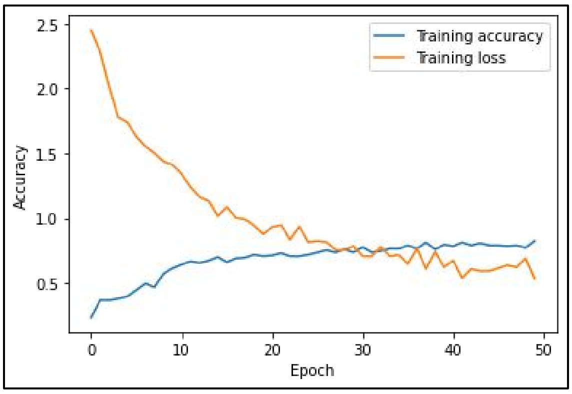


Figure 5: Graph showing the training accuracy

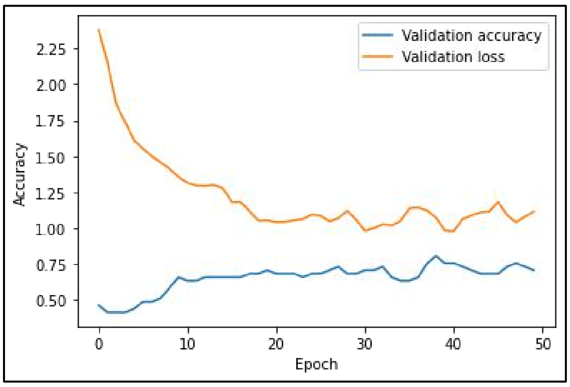


Figure 6: Graph showing the testing accuracy

B. Validating the Proposed CNN model

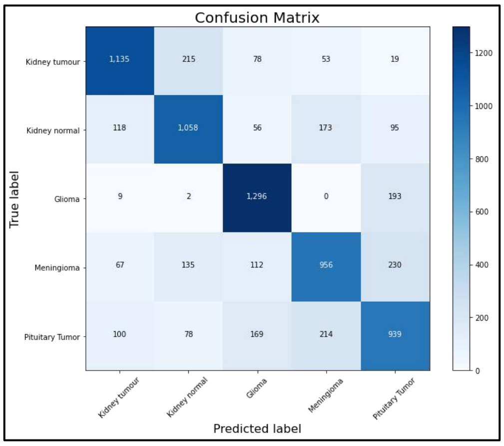


Figure 7: Heatmap of the confusion matrix

Figure 7 displays a heat map of the confusion matrix used to validate the model. The developed model is validated for 30% of the dataset which is about 7500 images. By selecting 1500 images from each of the labels, the model is verified. Out of 7500 images, the model correctly classified 5384 images by the developed model. The proposed model successfully classifies 1135 out of 1500 images with the label "Kidney Tumor," 1058 out of 1500 images with the label "Kidney Normal," 1296 out of 1500 images with the label "Glioma," 956 out of 1500 images with the label "Meningioma," and 939 out of 1500 images with the label "Pituitary Tumor." The generated model can recognise Glioma label with the highest degree of accuracy, followed by Kidney Tumor, Kidney Normal, Pituitary Tumor, and then Meningioma label, according to the confusion matrix. The model can be used to identify and categorizes cancer using CT scan pictures, according on the overall observation.

V. Conclusion

The goal of this research was to develop a deep learning tool that could identify and categorize Kidney and Brain tumors as well as Gliomas, Meningiomas, and Pituitary tumors. This was accomplished by utilising the Python Torchivison package to build a convolutional neural network. Three convolutional layers and three pooling layers made up the CNN, and they were both activated using the ReLU function. 25000 CT scan pictures were used in the dataset. This was split into training and testing data at random. 70% of the photos, or 17500, were utilised for training, while 30%, or 7500, were used for testing. Training accuracy for this model was 0.7895, and testing accuracy was 0.7561. A proposed model's practical applicability is one of its strongest points. 1500 photos from each class make up the 7500 test images used to validate the proposed model. 5384 out of 7500 photos were successfully identified by the generated model out of 7500 total images. The suggested model accurately identified 1135 out of 1500 photos as "Kidney Tumor," 1058 out of 1500 images as "Kidney Normal," 1296 out of 1500 images as "Glioma," 956 out of 1500 images as "Meningioma," and 939 out of 1500 images as "Pituitary Tumor." The proposed model may be utilized for the detection and classification of brain and kidney cancer from the CT scan pictures after considering the accuracy and precision.

A. Future Scope

This method may one day be used to identify and categories various cancers, including cervical cancer, colon cancer, acute lymphoblastic leukaemia, and others. To make this programme a useful tool for individuals to use for self-diagnosis, it can also be integrated into hardware.

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